

# Trade Credit and Relationships\*

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## Abstract

Most domestic and international firm-to-firm transactions rely on trade credit, where sellers grant buyers time to pay the invoice after delivery. Exploiting Chilean and Colombian transaction-level trade data, this paper documents new facts about trade credit use: trade credit use increases with firm-to-firm relationship length, an effect that is stronger for destination (source) countries with weaker (stronger) contract enforcement and for trade in differentiated goods. The paper develops a model featuring enforcement frictions, learning, and a financing cost advantage of trade credit that can rationalize these patterns. Initially, as there is uncertainty about the reliability of the trading partner, payment risk is a key factor limiting the use of trade credit. Through learning, this uncertainty resolves within a relationship over time. For older relationships, the payment choice is, therefore, only determined by the financing cost advantage of trade credit, and all relationships rely on trade credit in the long run. The paper thereby suggests a new benefit of long-term trade relationships: the ability to save on financing costs through the use of trade credit.

**Keywords:** trade credit, relationships, learning, financing costs, risk

**JEL Classification:** F12, F14, G21, G32

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\*This paper builds on and expands on results in the previously circulated paper “Trade Credit, Markups, and Relationships”, [Garcia-Marin, Justel and Schmidt-Eisenlohr \(2020\)](#). The views expressed are the authors’ and do not necessarily represent the views of the Federal Open Market Committee, its principals, or the Board of Governors of the Federal Reserve System.

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# 1 Introduction

Most domestic and international firm-to-firm transactions rely on trade credit, where sellers grant buyers time to pay the invoice after delivery.<sup>1</sup> As a consequence, trade credit is the most important source of short-term finance (Rajan and Zingales, 1998), and its availability has important consequences for the structure of global value chains (Kalemli-Ozcan et al., 2014; Antràs, 2023; Kim and Shin, 2023), trade flows (Amiti and Weinstein, 2011), the transmission of shocks within networks (Jacobson and von Schedvin, 2015), and macroeconomic stability (Hardy et al., 2022).

When do firms provide trade credit to their customers? While earlier work on domestic and international trade credit has identified key determinants across firms, products, and countries (see e.g. Giannetti et al., 2011; Ahn, 2014; Antràs and Foley, 2015; Demir and Javorcik, 2018; Giannetti et al., 2021), the role of relationship dynamics is less well understood.<sup>2</sup> At the same time, a growing literature in international trade has argued that relationships are central to both domestic and international trade (Bernard and Moxnes, 2018). Motivated by these observations, this paper uses transaction-level international trade data from Colombia and Chile to shed light on the link between trade credit and relationships. It shows how firm-to-firm relationships affect the provision of trade credit and develops a theory featuring enforcement frictions, learning, and a financing cost advantage of trade credit to rationalize the observed patterns. The model implies a new benefit of long-term trade relationships: the ability to save on financing costs through the use of trade credit.

The paper starts by documenting a striking positive relationship between trade credit use and relationship length (illustrated in Figure 1 for Colombia). The longer a Colombian firm is importing from a given foreign supplier, the more likely that supplier will provide trade credit to the Colombian importer. Correspondingly, the longer a Chilean exporter is

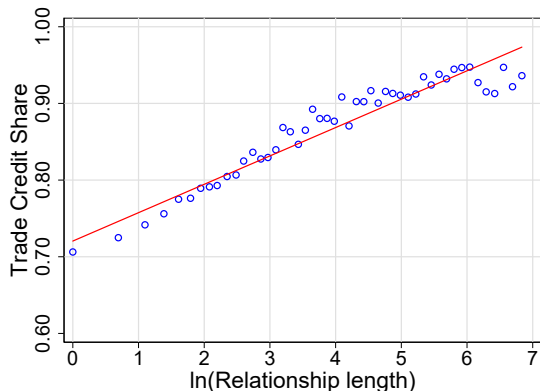
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<sup>1</sup>Trade credit is also referred to as open account. In balance sheet data, trade credit is reflected in accounts payable (trade credit received) and accounts receivable (trade credit granted).

<sup>2</sup>An important exception is Antràs and Foley (2015), who obtained detailed data from a large U.S. food exporter to study the payment terms that the firm grants to its foreign buyers over time. We discuss this paper in detail below.

exporting a product to a given destination country, the more likely it provides trade credit to its foreign buyer.

Figure 1. Trade Credit Increases with Relationship Length



*Notes:* The figure shows a binscatter diagram between trade credit share and (log) relationship length for Colombian imports. Relationship length is measured by the number of transactions between a Colombian importing firm and a foreign supplier.

Exploiting the rich information contained in the two transaction-level data sets, we generate additional facts that help us to zoom in on the mechanism behind this striking pattern: First, while firms switch their payment terms within a relationship from cash in advance to trade credit quite frequently, they rarely switch in the opposite direction. Second, relationship length affects the payment choice more for trade with high (low) rule-of-law source (destination) countries and for trade in differentiated products. Third, trade credit use increases rapidly at the beginning of relationships and tends to level off as relationships age. Finally, learning (proxied by relationship length) is particularly important for the trade credit choice in younger relationships, whereas the financing cost advantage (proxied by estimated markups) dominates the choice in older relationships.

The paper presents a model of trade credit choice that can rationalize these facts in a setup that combines a financing cost advantage of trade credit as in [Garcia-Marin et al. \(2023\)](#) with elements of the learning model in [Antràs and Foley \(2015\)](#). A financing cost advantage

of trade credit arises when exporters charge positive markups to importers, and there are financial frictions such that the borrowing rate exceeds the deposit rate. Then, trade credit has lower financing costs than cash in advance because it requires less gross borrowing – for cash in advance, the importer needs to borrow the full invoice amount, whereas, under trade credit, the exporter only needs to finance the production costs. Learning matters in the model because there are two types of firms, reliable and unreliable, and because of commitment problems that arise under both payment terms: A buyer may not pay after receiving goods on trade credit, and a seller may not deliver after getting paid cash in advance.

Through repeated interactions, firms can learn about the type of their trading partner. As firms learn, the importance of the commitment problem declines and the financing cost advantage of trade credit starts to dominate. Consequently, a sizable fraction of new relationships rely on cash in advance. In contrast, transactions within old firm-to-firm relationships are exclusively based on trade credit (as in Figure 1). As trade credit has a financing cost advantage over cash in advance, the model, therefore, implies a new benefit of long-term trade relationships: the ability to save on financing costs by employing the most efficient payment term, trade credit.

**Literature** The analysis speaks to two strands of the literature: the literature studying relationships and learning and the work on trade credit and international trade finance.

There is an increasing understanding that firm-to-firm relationships are central to international trade. A growing number of empirical papers have contributed to this assessment, relying increasingly on ‘two-sided’ trade data, where buyers and sellers have unique identifiers, allowing a deeper dive into global value chains than earlier work that relied on data where only one firm was identified (see [Bernard and Moxnes, 2018](#), for a survey).<sup>3</sup> This paper adds to this literature by looking at trade credit use within Colombian import relationships at the firm-pair level. The paper also contributes to the literature on learning and

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<sup>3</sup>See, also [Blum et al. \(2013\)](#), [Eaton et al. \(2014\)](#), [Kamal and Sundaram \(2016\)](#), [Monarch \(2022\)](#), [Bernard et al. \(2018\)](#), [Benguria \(2021\)](#), [Carballo et al. \(2018\)](#), [Heise \(2015\)](#), and [Monarch and Schmidt-Eisenlohr \(2018\)](#)

international trade, which has argued for an important role of learning about demand or supply factors, as well as about trading partners. The learning model in the present paper is based on the idea of learning about trading partners and directly builds on earlier work by [Araujo et al. \(2016\)](#) and [Antràs and Foley \(2015\)](#).<sup>4</sup>

The analysis suggests an additional benefit of long-term relationships: the ability to save on financing costs by employing the most efficient payment term, trade credit. This adds to earlier work that showed that long-term relationships trade more, have higher survival rates, are more resilient in crisis times ([Monarch and Schmidt-Eisenlohr, 2018](#)), are better able to share risk in the presence of exchange-rate shocks ([Heise, 2015](#)), and can overcome enforcement frictions ([Macchiavello and Morjaria, 2015](#)).

Several papers study payment terms theoretically in an international context ([Schmidt-Eisenlohr, 2013](#); [Ahn, 2014](#); [Antràs and Foley, 2015](#); [Niepmann and Schmidt-Eisenlohr, 2017a](#); [Fischer, 2020](#)). This paper adds to this literature by providing a joint analysis of learning dynamics and a financing cost advantage of trade credit and showing how these two channels interact in a meaningful way to explain the empirical patterns we uncover. This paper also extends the empirical literature on payment choice in international trade (see, e.g., [Ahn, 2014](#); [Antràs and Foley, 2015](#); [Hoefele et al., 2016](#); [Niepmann and Schmidt-Eisenlohr, 2017b](#); [Demir and Javorcik, 2018](#); [Garcia-Marin et al., 2023](#)) by generating new facts on trade credit use within relationships for the universes of Chilean and Colombian export and import transactions, respectively. More broadly, the paper adds to the work on trade and financial frictions (see e.g. [Ahn et al., 2011](#); [Amiti and Weinstein, 2011](#); [Manova, 2013](#); [Paravisini et al., 2015](#); [Niepmann and Schmidt-Eisenlohr, 2017b](#); [Leibovici, 2021](#)).

The closest paper to our knowledge is [Antràs and Foley \(2015\)](#). The findings in this paper expand both empirically and theoretically on this earlier paper, which studied sales of a single large U.S. poultry exporter and found that the firm’s sales to a specific customer

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<sup>4</sup>For papers on the broader topic of learning and entry, see also [Impullitti et al. \(2013\)](#), [Besedeš and Prusa \(2006\)](#), [Berthou \(2008\)](#), [Timoshenko \(2015a\)](#), and [Timoshenko \(2015b\)](#). Other paper on international trade and learning include [Albornoz et al. \(2012\)](#), [Ruhl and Willis \(2017\)](#), [Arkolakis et al. \(2018\)](#), and [Bastos et al. \(2018\)](#).

location shifted towards trade credit over time. First, it documents that trade credit use increases with the number of transactions at the firm-to-firm relationship level in data that covers the universe of Colombian import transactions. Second, in the model developed in this paper, the use of trade credit increases with relationship length even if there is a commitment problem on the seller side, which [Antràs and Foley \(2015\)](#) abstracted from. This more general result only holds when there is a financing cost advantage of trade credit as in [Garcia-Marin et al. \(2023\)](#). In the absence of this additional channel, learning eliminates the enforcement friction but does not deliver a clear prediction on the preference between trade credit and cash in advance.<sup>5</sup>

The remainder of the paper is organized as follows. Section 2 presents the model of payment choice and derives the main testable predictions. Section 3 describes the data. Section 4 discusses the empirical specifications we use to test the predictions of the model. Section 5 presents the empirical results. Finally, Section 6 discusses implications and routes for future research.

## 2 A Model of Trade Credit and Relationships

In this section, we develop a model of trade finance that features learning dynamics as in [Antràs and Foley \(2015\)](#) and a financing cost advantage of trade credit as in [Garcia-Marin et al. \(2023\)](#). As we show in the following, both mechanisms are needed jointly to rationalize the dynamic patterns we uncover in the data.

### 2.1 Baseline Model

One exporter is matched with one importer. Both firms are risk-neutral. There are two periods. In period 0, the exporter produces the goods and sends them to the importer.

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<sup>5</sup>Assuming that firms' financing costs for exporters and importers are drawn from similar distributions, the model in [Schmidt-Eisenlohr \(2013\)](#) and [Antràs and Foley \(2015\)](#) predicts that, in the absence of enforcement frictions, both cash in advance and trade credit would be used for an equal share of transactions.

In period 1, the importer sells the goods to a final consumer. Because of this time gap between production and final sale, firms need to agree on payment terms. Firms have two options. First, importers can pay in advance (cash in advance) before receiving the goods. Second, importers can pay after delivery (on trade credit). An exporter produces output for a total cost of  $C$  and sells it to the importer. The importer can then sell the goods to final consumers and generate revenues  $R$ . To finance their transactions, the exporter (importer) can borrow from banks at an interest rate  $r_b$  ( $r_b^*$ ), and deposit surplus funds at banks for a deposit rate of  $r_d$ .<sup>6</sup> Assume that the borrowing rates  $r_b$  and  $r_b^*$  exceed the deposit rate  $r_d$ .<sup>7</sup> For all endogenous variables (profits, payment) we use the sub-index “I” for the importer and sub-index “E” for the exporter.

The exporter makes a take-it-or-leave-it offer to the importer, who can choose to accept or reject the offer. Additionally assume that firms charge a constant markup over production costs to final consumers given by  $\mu$  so that  $R = \mu C$ . Throughout the analysis, we focus on the interesting case where the markup,  $\mu$ , is sufficiently large such that both trade credit and cash in advance generate positive profits,  $R > (1 + r_b)C$  and  $R > (1 + r_b^*)C$ , which implies  $\mu > 1 + r_b$  and  $\mu > 1 + r_b^*$ . Let  $\Pi_j^i$  denote the profit of the importer or exporter ( $j \in \{I, E\}$ ) under trade credit or cash in advance ( $i \in \{TC, CIA\}$ ).

**Diversion risk** Each payment term gives rise to a commitment problem: Importers that receive trade credit may divert goods without paying, and exporters that receive advance payments may divert cash without delivering the goods.<sup>8</sup> Assume that a fraction  $\eta$  ( $\eta^*$ ) of exporters (importers) is reliable; that is, these firms always fulfill their contracts. If a firm is unreliable, it does not fulfill its contract voluntarily but diverts goods or funds whenever it gets the opportunity to do so. Assume that an unreliable exporter and importer get the

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<sup>6</sup>The assumption that the exporter’s outside option is the deposit rate could be relaxed, as the mechanism works as long as the exporter’s marginal return to capital is below the importer’s borrowing rate.

<sup>7</sup>This interest rate spread can, for example, be rationalized by banks’ overhead costs. Alternatively, it can be micro-founded in a model with diversion risk (see [Garcia-Marin et al. \(2023\)](#)).

<sup>8</sup>In contrast to [Burkart and Ellingsen \(2004\)](#), we do not assume that goods are harder to divert than cash. Introducing this asymmetry would provide an additional rationale to use trade credit rather than cash in advance.

opportunity to divert goods or funds with probability  $1 - \phi > 0$  and  $1 - \phi^* > 0$ , respectively. Throughout the analysis, we focus on the case where it is optimal for unreliable firms to imitate reliable firms.<sup>9</sup>

**Trade Credit** Under trade credit, the exporter maximizes:

$$\begin{aligned} \text{E}[\Pi_{RS}^{TC}] &= \tilde{\eta}^* P^{TC} - (1 + r_b)C, \\ \text{s.t. } \text{E}[\Pi_{RB}^{TC}] &= R - P^{TC} \geq 0, \end{aligned}$$

where  $\tilde{\eta}^* = \eta^* + (1 - \eta^*)\phi^*$  is the expected probability of payment and  $P^{TC}$  is the payment from the importer to the exporter. Under trade credit, a reliable exporter gets paid  $P^{TC}$  with probability  $\tilde{\eta}^*$ , while she incurs production costs  $C$  with certainty. Because production takes place in period 0 while sales only occur in period 1, the exporter has to borrow the production costs  $C$  from a bank and pay the interest rate  $r_b$ . The maximization is subject to the participation constraint of the importer. Solving for the optimal payment,  $P^{TC}$ , that respects the participation constraint implies  $P^{TC} = R$ , delivering profits of:

$$\text{E}[\Pi_{RS}^{TC}] = \tilde{\eta}^* R - (1 + r_b)C. \quad (1)$$

**Cash in Advance** Under cash in advance, the exporter maximizes:

$$\begin{aligned} \text{E}[\Pi_{RS}^{CIA}] &= (1 + r_d)(P^{CIA} - C), \\ \text{s.t. } \text{E}[\Pi_I^{CIA}] &= \tilde{\eta}R - (1 + r_b^*)P^{CIA} \geq 0, \end{aligned}$$

with  $\tilde{\eta} = \eta + (1 - \eta)\phi$ . In period 0 the exporter gets paid  $P^{CIA}$  and incurs production costs  $C$ . As the price charged to the importer exceeds production costs, the exporter deposits the

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<sup>9</sup>Garcia-Marin et al. (2023) show that for a sufficiently high shares of reliable firms,  $\eta$  ( $\eta^*$ ), this pooling case is consistent with optimal behavior by both types of firms. Then, it is sufficient to derive the optimal choice of a reliable firm.



surplus funds at a bank for interest rate  $r_d$ . Under cash in advance, there is a risk that an importer is matched with an unreliable exporter who may not deliver the goods. Thus, the importer generates revenues  $R$  only with probability  $\tilde{\eta}$ . The importer pays  $P^{CIA}$  in period 0, borrowing from a bank at interest rate  $r_b^*$ . Solving for the optimal payment,  $P^{CIA}$ , that makes the importer's participation constraint bind, delivers  $P^{CIA} = \frac{\tilde{\eta}}{1+r_b^*}R$ . With expected exporter profits of:

$$E[\Pi_{RS}^{CIA}] = (1 + r_d) \left( \frac{\tilde{\eta}}{1 + r_b^*} R - C \right). \quad (2)$$

This represents the general solution for all exporters, as we assumed that conditions are such that an unreliable exporter always imitates a reliable exporter.

## 2.2 Trade Credit and Repeated Interactions

Consider now the case where an importer and an exporter interact repeatedly. Importantly, we assume that an exporter cannot offer a dynamic contract to solve the commitment problem.<sup>10</sup> However, as they interact repeatedly, firms update their belief about each other's reliability. Assume that with every successful transaction, a firm's belief about its trading partner's reliability improves. That is, assume that  $\partial\eta_k/\partial k > 0$  ( $\partial\eta_k^*/\partial k > 0$ ), where  $k$  is the number of previous interactions and  $\eta_k$  ( $\eta_k^*$ ) is the probability that an exporter (importer) is reliable after  $k$  interactions. Note that the dynamics do not necessarily have to arise from learning about the trading partner's reliability. Any dynamic process that raises the expected reliability of the trading partner over time would generate similar predictions. For example, firms may be more willing to fulfill their contracts due to relationship-specific investments or learning-by-doing. In appendix A.1, we provide one example of Bayesian learning that can micro-found the assumed learning dynamics.<sup>11</sup>

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<sup>10</sup>See [Schmidt-Eisenlohr \(2011\)](#), [Olsen \(2016\)](#), and [Fischer \(2020\)](#) for an analysis of optimal dynamic contracts in this environment.

<sup>11</sup>The micro-foundation in appendix A.1 is also used in [Araujo and Ornelas \(2007\)](#), [Antràs and Foley \(2015\)](#), [Macchiavello and Morjaria \(2015\)](#) and [Monarch and Schmidt-Eisenlohr \(2018\)](#).

We allow the speed of learning to differ between importers and exporters, with  $\eta_k^*$  and  $\eta_k$ , representing the belief about the probability that an importer or exporter is reliable after  $k$  interactions, respectively. The optimal payment choice is then determined by:

$$\frac{\Pi_E^{TC} - \Pi_E^{CIA}}{C} = \frac{\Delta\Pi_E}{C} = \tilde{\eta}_k^* \mu - (1 + r_b) - (1 + r_d) \left( \frac{\tilde{\eta}_k}{1 + r_b^*} \mu - 1 \right).$$

where  $\tilde{\eta}_k$  and  $\tilde{\eta}_k^*$  are increasing in the number of previous interactions  $k$ , as  $\eta$  and  $\eta^*$  increase.

Taking the derivative with respect to  $k$  delivers:

$$\frac{\partial(\Delta\Pi_E/C)}{\partial k} = \mu \left( (1 - \phi^*) \frac{\partial\eta_k^*}{\partial k} - \frac{1 + r_d}{1 + r_b^*} (1 - \phi) \frac{\partial\eta_k}{\partial k} \right). \quad (3)$$

This derivative is positive if  $\frac{\partial\eta_k^*}{\partial k} > \frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial\eta_k}{\partial k}$ . If learning about the importer is sufficiently fast relative to learning about the exporter, then trade credit becomes more attractive as two firms repeatedly trade with each other. Learning about the importer is key because the commitment problem under trade credit only depends on the reliability of the importer ( $\eta_k^*$ ). Thus, for the financing cost advantage of trade credit to dominate over time, the commitment problem under trade credit needs to decline through learning about the importer. Specifically, learning about the importer cannot be too slow relative to learning about the exporter, as the latter makes cash in advance more attractive. Importantly, the condition implied by (3) allows for some asymmetry in the speed of learning, that is trade credit use increases with relationship length even if learning about the exporter is a bit faster (as long as  $r_b^* > r_d$ ).<sup>12</sup> This result is summarized in Proposition 1.

**Proposition 1 (Trade Credit and Learning)**

*Suppose learning about the importer is sufficiently fast, that is:  $\frac{\partial\eta_k^*}{\partial k} > \frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial\eta_k}{\partial k}$ . Then, payment is more likely on trade credit terms, the longer the two firms have traded.*

**Proof.** Follows directly from equation (3). ■

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<sup>12</sup>The speed of learning could be a function of the payment terms. In particular, there could be more learning about the exporter under cash in advance and more learning about the importer under trade credit, due to the asymmetry in the commitment problem. For tractability, we focus on the case where learning is independent of the payment terms. The key assumption is that there is learning in both directions and that the speed of learning is not too dissimilar.

The proposition is quite intuitive. The longer two firms trade with each other, the more likely they will fulfill their contracts. The key advantage of trade credit is that it saves on financing costs as compared to cash in advance. Through learning, contract enforcement becomes less of an issue and financing costs differences matter more for the contract choice. Therefore, as firms learn that their trading partners are reliable, they increasingly prefer trade credit over cash in advance.

### 2.3 Trade Credit, Learning, and Enforcement

Does the strength of a country's institutions affect the relationship between repeated interactions and trade credit? This would be intuitive as learning works as a substitute for imperfect contract enforcement in the model. In particular, if contracts were perfectly enforceable, learning would not matter. To check for this mechanism in the model, start with equation (3) and take the cross-derivatives with respect to  $\phi$  and  $\phi^*$  to get:

$$\frac{\partial^2(\Delta\Pi/C)}{\partial k\partial\phi} = \mu \left( \underbrace{\frac{\partial\eta_k}{\partial k}}_{\text{Direct Effect}} \quad \underbrace{-(1-\phi)\frac{\partial^2\eta_k}{\partial k\partial\phi}}_{\text{Indirect Effect}} \right) \frac{1+r_d}{1+r_b^*}, \quad (4)$$

$$\frac{\partial^2(\Delta\Pi/C)}{\partial k\partial\phi^*} = \mu \left( \underbrace{-\frac{\partial\eta_k^*}{\partial k}}_{\text{Direct Effect}} \quad \underbrace{+(1-\phi^*)\frac{\partial^2\eta_k^*}{\partial k\partial\phi^*}}_{\text{Indirect Effect}} \right). \quad (5)$$

There are two effects. First, a direct effect: With better enforcement in the exporter (importer) country, learning makes trade credit more (less) attractive. To understand the intuition for the direct effect, recall that trade credit becomes more attractive as the exporter learns that the importer is more reliable (as trade credit creates the risk that the importer does not pay). Stronger enforcement in the exporter (importer) country reduces the importance of learning about the exporter (importer), which makes learning more about the importer (exporter) and hence increases (decreases) the effect of learning on trade credit.

The second effect depends on how the speed of learning changes with enforcement

$\left(\frac{\partial^2 \eta_k}{\partial k \partial \phi} \text{ and } \frac{\partial^2 \eta_k^*}{\partial k \partial \phi^*}\right)$ . Typically, with weaker enforcement, learning is faster initially but slower later on, such that the sign of the cross-derivative changes in  $k$ . However, one would typically expect the direct effect to dominate the indirect effect, which we put as a condition into the proposition below.

**Proposition 2**

*Suppose  $(1 - \phi) \frac{\partial^2 \eta_k}{\partial k \partial \phi} < \frac{\partial \eta_k}{\partial k}$  and  $(1 - \phi^*) \frac{\partial^2 \eta_k^*}{\partial k \partial \phi^*} < \frac{\partial \eta_k^*}{\partial k}$ . Then, the effect of learning on trade credit increases (decreases) in the strength of contract enforcement in the exporter (importer) country.*

**Proof.** Follows directly from equations (4) and (5). ■

## 2.4 Trade Credit, Learning, and Product Complexity

Does the effect of learning on trade credit vary across products of different complexity? This could be the case, because contract enforcement tends to be more difficult for more complex products, as courts may have a harder time verifying successful transactions. In particular, quality may be more difficult to check for more complex products. Following [Hoefele et al. \(2016\)](#), assume that product complexity is captured by parameter  $\gamma \in [0, 1]$ , where a higher  $\gamma$  represents a more complex product. Assume further that the exporter and importer now have an opportunity to divert funds or goods with probabilities  $\phi^\gamma$  and  $(\phi^*)^\gamma$ , respectively. That is, there are more opportunities for diversion when firms are trading in complex products. Focusing for tractability on the case with symmetric financing costs ( $r_b = r_b^*$ ) and symmetric contract enforcement ( $\phi = \phi^*$ ), the optimal decision becomes:

$$\frac{\Delta \Pi}{C} = \tilde{\eta}_k^*(\gamma) \mu - (1 + r_b) - (1 + r_d) \left( \frac{\tilde{\eta}_k(\gamma)}{1 + r_b} \mu - 1 \right).$$

with  $\tilde{\eta}_k(\gamma) = \eta_k + (1 - \eta_k)\phi^\gamma$  and  $\tilde{\eta}_k^*(\gamma) = \eta_k^* + (1 - \eta_k^*)\phi^\gamma$ . Taking the derivative with respect to  $k$  delivers:

$$\frac{\partial(\Delta \Pi / C)}{\partial k} = \mu(1 - \phi^\gamma) \left[ \frac{\partial \eta_k^*}{\partial k} - \frac{1 + r_d}{1 + r_b} \frac{\partial \eta_k}{\partial k} \right]. \tag{6}$$

Then taking the cross-derivative with respect to  $\gamma$  and rearranging delivers:

$$\frac{\partial^2(\Delta\Pi/C)}{\partial k\partial\gamma} = -\mu\phi^\gamma \left[ \frac{\partial\eta_k^*}{\partial k} - \frac{1+r_d}{1+r_b} \frac{\partial\eta_k}{\partial k} \right] \ln(\phi). \quad (7)$$

which is greater or equal to zero as  $\ln\phi \leq 0$ . That is, the effect of learning on the difference between trade credit and cash in advance is stronger for more complex products (higher  $\gamma$ ). This result is summarized in the following proposition:

**Proposition 3**

*Suppose the importer and the exporter face the same financing costs and enforcement frictions, and learning speeds are not too different ( $\frac{\partial\eta_k^*}{\partial k} > \frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial\eta_k}{\partial k}$ ). Then, trade credit use increases with relationship length, and the strength of this effect increases with the complexity of the product that is traded.*

**Proof.** Follows directly from equations (6) and (7). ■

Proposition 3 is quite intuitive: Contracts for more complex products are harder to enforce and hence learning, which reduces the need for contract enforcement, has a stronger effect on firms' payment choices.

## 2.5 Relationship Length and Markups

How do relationship length and markups interact? Recall that the model features two frictions: An enforcement problem and financial intermediation costs. These two frictions lead to two dynamic predictions that we derive formally below. First, the role of relationship lengths for the payment terms choice decreases over time, as firms learn about their trading partners and enforcement becomes less of a concern. Second, as enforcement frictions decline, the financial friction becomes relatively more important, making markups more central for the payment choice in older relationships.

**Trade Credit and a Declining Speed of Learning** Equation (3) shows that the difference in profits between trade credit and cash in advance increases with relationship length,

$k$ . Taking the second derivative of equation (3) with respect to relationship length  $k$  delivers:

$$\frac{\partial^2(\Delta\Pi_E/C)}{\partial k^2} = \mu \left( (1 - \phi^*) \frac{\partial^2 \eta_k^*}{\partial k^2} - \frac{1 + r_d}{1 + r_b^*} (1 - \phi) \frac{\partial^2 \eta_k}{\partial k^2} \right). \quad (8)$$

This derivative is negative if:  $-\frac{\partial^2 \eta_k^*}{\partial k^2} > -\frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial^2 \eta_k}{\partial k^2}$ . Now, assume that the speed of learning decreases over time, a standard feature of most types of learning,<sup>13</sup> and consider the case where the speed of learning is symmetric, so that:  $\frac{\partial^2 \eta_k^*}{\partial k^2} = \frac{\partial^2 \eta_k}{\partial k^2}$ . Then, the above condition simplifies to:  $(1 - \phi^*) > \frac{1+r_d}{1+r_b^*} (1 - \phi)$ . In this case, the effect of repeated interactions on the trade credit choice declines over time as long as enforcement across countries is not too different and the borrowing rate exceeds the deposit rate,  $r_b^* > r_d$ .

**Trade Credit, Learning, and Markups** Next, take the cross-derivative of equation (3) with respect to the markup  $\mu$  to get:

$$\frac{\partial^2(\Delta\Pi_E/C)}{\partial k \partial \mu} = \left( (1 - \phi^*) \frac{\partial \eta_k^*}{\partial k} - \frac{1 + r_d}{1 + r_b^*} (1 - \phi) \frac{\partial \eta_k}{\partial k} \right), \quad (9)$$

which is positive if:  $\frac{\partial \eta_k^*}{\partial k} > \frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial \eta_k}{\partial k}$ . The following proposition summarizes the two results on the speed of learning and on learning and markups:

**Proposition 4 (Repeated Interactions, Learning, and Markups)**

1. *Suppose the speed of learning declines in the length of a relationship and learning speeds are not too different ( $-\frac{\partial^2 \eta_k^*}{\partial k^2} > -\frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial^2 \eta_k}{\partial k^2}$ ). Then, the effect of learning on the payment choice declines in the number of interactions  $k$ .*
2. *Suppose learning speeds are not too different ( $\frac{\partial \eta_k^*}{\partial k} > \frac{1+r_d}{1+r_b^*} \frac{1-\phi}{1-\phi^*} \frac{\partial \eta_k}{\partial k}$ ). Then, the effect of the markup on the payment choice increases with the number of interactions  $k$ .*

**Proof.** Follows directly from equations (8) and (9). ■

Proposition 4 formalizes the intuition provided at the beginning of this section. As firms continually trade with each other, learning becomes less important and financing costs and

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<sup>13</sup>See appendix A.1 for details on how to micro found this assumption with a model of Bayesian learning.

therefore markups become more important for choosing the payment term. In the limit, when a firm has perfectly learned the type of its trading partner, the payment choice only depends on financing costs and thus trade credit tends to dominate. Importantly, Proposition 4 provides clear testable predictions for this mechanism that we can take to the data.

### 3 Data

Our primary dataset is transaction-level import data from Colombia from 2007-2016. A key advantage of the Colombian data is that it provides firm identifiers for both Colombian importers and foreign exporters, which allows studying relationships at the importer-exporter-(product) level. This information is crucial for testing how payment choices change as relationships evolve.

In addition, we use transaction-level export data from Chile for 2003-2007 to confirm the model's predictions on markups. In the Chilean data, only exporters are identified at the firm level, while importers can only be identified as a country-HS8 pair. However, the Chilean customs data can be matched to manufacturing survey data that allows estimating markups and productivity at the firm-product level. We describe both Colombian and Chilean data in detail next.

#### 3.1 Colombian Import Data

Data for Colombian imports is collected by the Colombian customs agency, DIAN (*Dirección de Impuestos y Aduanas Nacionales*), and records the universe of international transactions entering the country. For each transaction, the data provides information on the importer's tax ID and the name and address of the exporting firm in the source country. Importantly, the identifying variables for importers and exporters are recorded consistently across years, allowing us to track these firms uniquely over the sample period. For each transaction, the data details the transaction date, the 10-digit HS code to which the product belongs,

the FOB value of the merchandise, and the financing mode of the import transaction. In particular, the data contain information allowing us to determine if the transaction was paid post-shipment (trade credit), with cash in advance, a letter of credit, or other payment terms.

We create a consistent identifier for foreign exporters to Colombia following [Benguria \(2021, 2022\)](#). This procedure follows the method used by the U.S. Census Bureau to identify foreign suppliers in US imports as described by [Kamal and Monarch \(2018\)](#). Specifically, a foreign exporter ID is constructed as a string combining a two-digit ISO country code, the first three characters of the city in which the exporter is located, the first three characters in the first word of the exporter's name, the first three characters in the second word of the exporter's name, and the first four characters in the first number found on the street address of the exporter.<sup>14</sup>

We aggregate the data such that each observation corresponds to a Colombian importer, foreign exporter, HS10 product, and day.<sup>15</sup> We refer to these observations as transactions. We exclude from the sample transactions that do not involve a payment as well as transactions with payment terms other than trade credit, cash in advance, or letters of credit. The transactions excluded account for 14.3% of the total. The sample used in the analysis has 15.2 million transactions.

## 3.2 Matched Production-Export Data for Chile

Transaction-level export data for Chile is provided by the Chilean National Customs Service and is available for the 90 main destinations of Chilean exports, accounting for over 99.7% of the value of overall national exports in our sample period. For each export transaction, the dataset details the identity of the exporting firm, the destination country, the 8-digit HS code to which the product belongs, the date of the transaction, the FOB value of the merchandise,

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<sup>14</sup>This procedure is implemented after removing punctuation marks from names and addresses and standardizing common prefixes and suffixes such as "inc", "llc", etc.

<sup>15</sup>In the raw data, in some cases a firm has multiple transactions of the same product in the same day



and the financing mode of the export transaction (trade credit, cash in advance, letters of credit, or other payment terms).

We merge the export dataset with the Chilean Annual Manufacturing Survey (ENIA), which provides production information. ENIA is collected by Chilean National Statistical Agency (INE) and covers the universe of manufacturing entities with 10 or more employees. It surveys approximately 5,000 manufacturing establishments annually, of which approximately 20 percent are exporters. Firms in ENIA are identified with the same identifier provided in the Customs data, allowing us to match both datasets. ENIA provides detailed information on firm level outcomes (e.g., sales, inputs expenditures, employment, investment), on each product sold by each firm (value and volume), and on each input purchased by each firm (value and volume), which we use in our computation of markups.

We aggregate the data such that each observation corresponds to a Chilean exporter, HSS product, destination, and day, and to these observations as transactions. As with the Colombian data, we exclude from the sample transactions that do not involve a payment as well as transactions with payment terms other than trade credit, cash in advance, or letters of credit. These excluded transactions account for 0.6% of the total. The sample used in the analysis has 604 thousand transactions, and accounts for approximately 80% of the value of Chilean (non-copper) exports.

## 4 Empirical Approach

This section presents the empirical methodology we follow for testing the predictions on trade credit and relationship length.

### 4.1 Relationship Definition

To test the predictions of the model, we define relationships in two ways. In the Colombian import data, we define a relationship as all interactions that take place within an importer-

exporter firm pair. Our version of the Chilean export data does not have information about the importer in the destination country. Therefore, we define relationships in that dataset at the exporter-product-destination country level. That is, a relationship encompasses all exports of a Chilean firm of the same product to the same destination country.

## 4.2 Trade Credit and Relationship Length

Proposition 1 predicts that the use of trade credit increases in the length of a trading relationship. To test this prediction, we use transaction-level trade data which allow us to include a large set of granular fixed effects. Considering our baseline sample of Colombian imports, the main regression exploits within-relationship variation and takes the following form:

$$\rho_{iept} = \alpha_1 \ln(\text{Rel. Length})_{iet} + \psi_{iep} + \nu_{iept}, \quad (10)$$

where  $\rho_{iept}$  is a dummy variable that equals one if a transaction between Colombian importer  $i$  and foreign exporter  $e$  in product  $p$  on day  $t$  is settled with trade credit and zero otherwise.  $\text{Rel. Length}_{iet}$  captures the length of a relationship. It is calculated as the cumulative number of transactions between importer  $i$  and exporter  $e$  through date  $t$ . Specification (10) controls for importer–exporter–product fixed-effects ( $\psi_{iep}$ ). In alternative specifications, we also include importer-product-year and/or exporter–year fixed-effects. Proposition 1 predicts that  $\alpha_1 > 0$ : The use of trade credit should increase in the length of the relationship.<sup>16</sup>

**Interactions with Country and Product Characteristics** To test Proposition 2 on learning and contract enforcement, we modify specification (10), adding interactions between

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<sup>16</sup>We also test Proposition 1 using the Chilean export data, estimating:

$$\rho_{edpt} = \alpha_1 \ln(\text{Rel. Length})_{edpt} + \psi_{edp} + \nu_{edpt}, \quad (11)$$

Now,  $\rho_{edpt}$  equals one if exporter  $e$  exports product  $p$  to destination country  $d$  on date  $t$  using trade credit and zero otherwise. Because we do not observe the identity of the importing firm in the Chilean export data, relationship length is computed as the cumulative number of transactions of exporter  $e$  of product  $p$  to destination  $d$  through date  $t$ .

the length of the relationship and contract enforcement in the source country  $s$ :

$$\begin{aligned} \rho_{iept} = & \alpha_1 \ln(\text{Rel. Length})_{iet} \times \text{High Enf.}_s + \alpha_2 \ln(\text{Rel. Length})_{iet} \times \text{Low Enf.}_s \\ & + \psi_{iep} + \nu_{iept}, \end{aligned} \quad (12)$$

where  $\text{High Enf.}_s$  and  $\text{Low Enf.}_s$  are dummy variables that equal one if a source country  $s$  has an above and below median value of contract enforcement, respectively, and are zero otherwise. Proposition 2 predicts that  $\alpha_1 < \alpha_2$ : The effect of learning on trade credit use should be stronger in imports from source countries with weaker contract enforcement.<sup>17</sup>

Finally, when testing the predictions of Proposition 3 on product complexity, we modify specification (10) again, interacting  $\ln(\text{Rel. Length})_{iet}$  with dummy variables that indicate whether a product is homogeneous ( $\text{Homog}_p$ ) or differentiated ( $\text{Diff}_p$ ) according to the Rauch (1999) product classification:<sup>18</sup>

$$\begin{aligned} \rho_{iept} = & \alpha_1 \ln(\text{Rel. Length})_{iet} \times \text{Homog}_p + \alpha_2 \ln(\text{Rel. Length})_{iet} \times \text{Diff}_p \\ & + \psi_{iep} + \nu_{iept}, \end{aligned} \quad (14)$$

Proposition 3 predicts that  $\alpha_2 > \alpha_1$ , that is, the use of trade credit should increase more with relationship length for imports of differentiated products, as there is more scope for learning.<sup>19</sup>

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<sup>17</sup>We also test Proposition 2 using the Chilean export data, estimating:

$$\begin{aligned} \rho_{edpt} = & \alpha_1 \ln(\text{Rel. Length})_{edpt} \times \text{High Enf.}_d + \alpha_2 \ln(\text{Rel. Length})_{edpt} \times \text{Low Enf.}_d \\ & + \psi_{edp} + \nu_{edpt}, \end{aligned} \quad (13)$$

where  $\text{High Enf.}_d$  and  $\text{Low Enf.}_d$  are dummy variables that indicate high or low levels of contract enforcement in destination country  $d$ . In this case, the theory predicts that the effect of learning on trade credit use should be weaker for exports to destinations with weaker contract enforcement, that is,  $\alpha_1 > \alpha_2$ .

<sup>18</sup>We classify as homogeneous products those that are traded on an organized exchange or that have a reference price.

<sup>19</sup>We also test Proposition 3 using the Chilean export data, estimating:

$$\begin{aligned} \rho_{edpt} = & \alpha_1 \ln(\text{Rel. Length})_{edpt} \times \text{Homog}_p + \alpha_2 \ln(\text{Rel. Length})_{edpt} \times \text{Diff}_p \\ & + \psi_{edp} + \nu_{edpt}, \end{aligned} \quad (15)$$

Proposition 3 implies  $\alpha_2 > \alpha_1$ , the same as for imports.

### 4.3 Trade Credit, Learning, and Markups

Proposition 4 predicts that the effect of learning on the trade credit choice declines with the number of transactions, whereas the effect of the financing cost advantage increases with the number of transactions. To test these predictions, we estimate the following specification for different subsamples:

$$\rho_{edpt} = \alpha_1 \ln(\text{Rel. Length})_{edpt} + \alpha_2 \ln(\text{Markups})_{ipt} + \psi_{edp} + \nu_{edpt}, \quad (16)$$

As the information needed to estimate markups and productivity is only available in the Chilean manufacturing survey, we focus this part of our analysis on Chilean export data.

Proposition 4 predicts a higher magnitude for  $\alpha_1$  early on in the relationships. In contrast, the magnitude for  $\alpha_2$  should increase with the number of transactions as the effect of learning becomes less important. We test this prediction by splitting the data between the first nine transactions in a relationship and all subsequent trades.

To address the endogeneity of markups, we follow [Garcia-Marin et al. \(2023\)](#) implementing a 2SLS strategy. Specifically, we use firm-product physical total factor productivity (TFPQ) as an instrument for markups. This instrument is consistent with (most) models with variable markups that predict that more efficient firms charge higher markups. When estimating the production function and computing TFPQ, we specify output and intermediate inputs in terms of physical units to avoid the so-called output and input price biases, which may lead to confound measured productivity and markups (see [De Loecker and Goldberg, 2014](#)). Appendix B.1 details the procedure for computing firm-product markups, which follows [De Loecker et al. \(2016\)](#).

## 5 Results

This section presents our empirical analysis. We start by providing descriptive evidence on the use of trade credit and other payment terms. We then provide econometric evidence on

the link between relationship length and payment terms, as well as results on trade credit and the interaction between relationship length and the strength of contract enforcement, product complexity, and markups. Finally, we discuss our robustness analysis.

## 5.1 Descriptive Evidence

We begin by comparing the shares of different payment terms in the overall sample in Table 1. Trade credit is the dominant payment term. About 87.4% of import transactions in Colombia are paid with trade credit, followed by cash in advance (10.8%) and letters of credit (1.8%).<sup>20</sup> We find a very similar pattern for Chilean exports in panel B.

Table 2 reports the frequency of each payment term for different points over the life cycle of a relationship. For both countries, trade credit shares for the first transaction are lowest and then rise over the life of a relationship. In the case of Colombia (see panel A), the first transaction in a relationship is paid with trade credit most of the time (73.7%), followed by cash in advance (23.9%). The use of trade credit increases to 79% and 82% in the fifth and tenth transactions of a relationship, respectively. From the eleventh transaction onward, the trade credit share reaches 89.9%, which is 16.2 percentage points higher than the trade credit share in the first transaction. Most of this increase in the trade credit share comes at the expense of cash in advance, whose share drops by 15.4 percentage points to reach 8.5%. The data on Chilean exports (see panel B) shows a similar pattern, with the trade credit share going from 80.8% in the first transaction to 90.9% from the eleventh transaction onward.

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<sup>20</sup>Recall that, as mentioned in Section 3, we exclude from our sample payment terms that do not fall under these three categories, so here we report percentages out of the total of the sum of these three categories.

Table 1. Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
<b>A. Colombian Imports</b>						
Trade Credit Dummy	87.4	33.2	100	100	100	15,216,853
Cash in Advance Dummy	10.8	31.1	0	0	0	15,216,853
Letter of Credit Dummy	1.8	13.3	0	0	0	15,216,853
Import Value	20743.9	272,095.2	223	1378	8230	15,216,853
<b>B. Chilean Exports</b>						
Trade Credit Dummy	89.1	31.1	100.0	100.0	100.0	604,843
Cash in advance Dummy	5.2	22.3	0.0	0.0	0.0	604,843
Letters of Credit Dummy	5.6	23.0	0.0	0.0	0.0	604,843
Export Value (US\$)	138,205	1,196,335	3,700.0	14,439.5	49,484.9	604,843

*Notes:* The table lists the summary statistics for the variables used in the paper’s baseline analysis sample. Panel A comprises transaction-level data for the universe of Colombian importers from 2007 to 2016. Panel B comprises transaction-level data for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA) from 2003 to 2007.

Table 2. Payment Terms and Relationship Length

	Trade Credit	Cash in Advance	Letter of Credit
<b>A. Colombian Imports</b>			
First transaction	73.7	23.9	2.3
Fifth transaction	79.0	18.7	2.3
Tenth transaction	82.0	15.9	2.1
Eleventh transaction and beyond	89.9	8.5	1.7
<b>B. Chilean Exports</b>			
First transaction	80.8	11.9	7.3
Fifth transaction	85.7	8.3	6.0
Tenth transaction	87.1	7.0	5.9
Eleventh transaction and beyond	90.9	3.8	5.3

*Notes:* The table shows the percentage of transactions financed through trade credit terms (column 1), cash in advance terms (column 2), letter of credit terms (column 3), and other forms of payment (column 4) in the first, fifth, or tenth transaction in a relationship.

Figure 2 provides further evidence on the link between payment terms and relationship length. It shows a binscatter plot for the logarithm of relationship length—defined as the log cumulative number of transactions occurring from the beginning of a relationship—and

the average use of the three main payment terms in Colombia (top panel) and Chile (bottom panel).

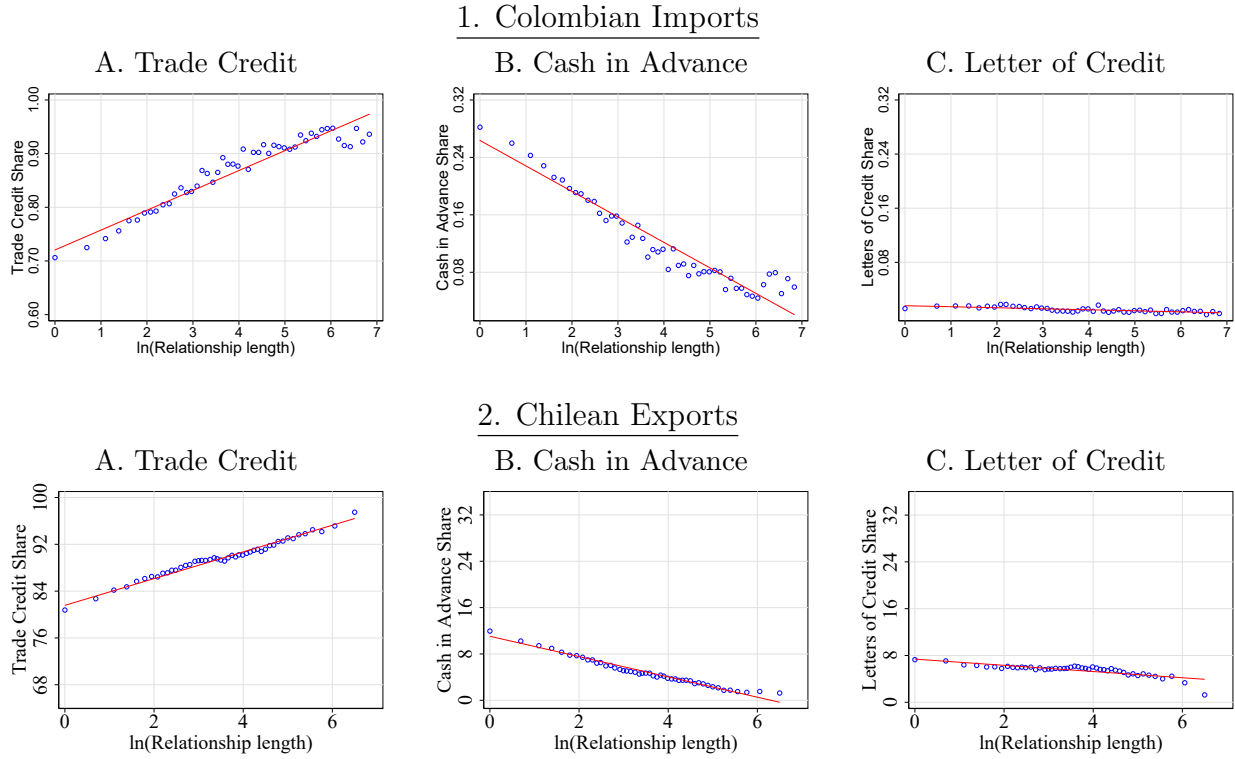
Chart A on the left of each panel shows that the use of trade credit increases almost monotonically with the length of the relationship. Chart B in the middle shows that the opposite occurs with the share of transactions paid cash in advance. Finally, Chart C on the right shows that the share of letters of credit also decreases with relationship length, but to a much lesser extent than cash in advance. This evidence is consistent with Proposition 1, suggesting that firms are more likely to use trade credit as they learn about the reliability of their trading partners.

We can also compute transition probabilities between payment terms in consecutive transactions within a relationship (see Table 3). For relationships that use cash in advance, it is common to transition to trade credit in the next transaction. In contrast, switches in the opposite direction, from trade credit to cash in advance, are very rare. For the case of Colombian imports (panel A), 7% of relationships that utilize cash in advance switch to trade credit for the next transaction, while only 0.8% of relationships that use trade credit switch to cash in advance. These patterns are qualitatively similar in the Chilean export data.

This asymmetric pattern, where many more relationships switch toward trade credit than toward other payment terms, is very consistent with the financing cost advantage of trade credit: as the enforcement friction wanes with relationship length and learning, the advantage of trade credit in terms of financing costs starts to dominate, generating switches from cash in advance to trade credit but not in the opposite direction. [Antràs and Foley \(2015\)](#) derive a similar prediction by assuming that there is no commitment problem for the seller, which seems plausible in their specific application to a big U.S. poultry exporter but is unrealistic when looking at the universe of importers or exporters. A generalization of their setup to two-sided learning generates symmetric switches of payment terms: If financing costs are lower in the importer (exporter) country, firms switch to cash in advance (trade credit) over

time. Only the financing cost advantage of trade credit introduces the asymmetry necessary to generate a broad-based increase in the use of trade credit within relationships over time in a model with two-sided learning.

Figure 2. Trade Credit Share and the Length of the Relationship



*Notes:* The figure plots the frequency of each of the three main payment terms in the Colombian and Chilean data for 50 bins of the measure of relationship length (defined as the cumulative number of transactions occurring from the beginning of the relationship).



Table 3. Transitions Between Payments Forms

	Payment term in $t + 1$ :		
	Trade Credit	Cash in Advance	Letter of Credit
A. Colombian Imports			
Payment term in $t$ :			
Trade Credit	99.1	0.8	0.1
Cash in Advance	7.0	92.9	0.2
Letter of Credit	7.6	1.2	91.2
B. Chilean Exports			
Payment term in $t$ :			
Trade Credit	94.9	2.7	2.4
Cash in advance	30.9	65.7	3.4
Letters of Credit	31.0	4.1	64.9

*Notes:* The table shows transition probabilities in payment terms within relationships. Consider any two consecutive transactions within a relationship labeled  $t$  and  $t + 1$ . Each cell shows the fraction of consecutive transactions that transition from the payment term shown in the corresponding row to the payment term shown in the corresponding column.

## 5.2 Main Results on Relationship Length

According to Proposition 1, trade credit use should increase with relationship length. Table 4 tests this prediction by estimating equation (10). Panel A reports results for Colombian imports. Column 1 includes importer-exporter-product fixed effects, while columns 2 and 3 sequentially add source country-year and firm-product-year fixed effects to control for country-specific and firm-product-specific time-varying shocks. Across all specifications, the coefficient on relationship length is positive and statistically significant, in line with Proposition 1.

One concern is that the results in Columns 1 to 3 may be affected by survival bias. This would bias results if, for example, short-lived relationships were less likely to rely on trade credit than longer-lasting relationships. To address this concern, column 4 re-estimates the specification in column 3, using a sample of the first twenty transactions in relationships with at least twenty trades. This sample – which we denote as ‘balanced’ – is not subject to survival bias because, by definition, all relations survive the entire sample period. The fact

that the coefficient in column 4 is positive and has a similar magnitude as the one in column 3, where the full sample is used, suggests that survival bias does not affect our results.

Panel B reports the results based on the sample of Chilean exports, where trade credit use also increases with relationship length. Even though the Chilean data measures relationships at a more aggregate level, the magnitudes in our preferred specifications, columns 3 and 4, are of similar magnitude across the two data sets.

Table 4. Relationship Length and Trade Credit Share

	(1)	(2)	(3)	(4)
<b>A. Colombian Imports</b>				
ln(Relationship Length)	0.283*** (0.023)	0.589*** (0.022)	0.412*** (0.016)	0.387*** (0.049)
Sample	All	All	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	—	Yes	Yes	Yes
Importer-HS10-Year FE	—	—	Yes	Yes
Observations	12,842,428	12,842,182	12,164,470	956,301
R <sup>2</sup>	0.75	0.75	0.83	0.83
<b>B. Chilean Exports</b>				
ln(Relationship Length)	1.443*** (0.120)	0.784*** (0.130)	0.924*** (0.121)	0.618*** (0.217)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	604,843	604,843	604,843	47,177
R <sup>2</sup>	0.67	0.68	0.73	0.72

*Notes:* This table shows the results of a transaction-level regression in which the dependent variable is  $(100 \times)$  a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The independent variable is relationship length, measured as the log of the cumulative count of transactions within a relationship. Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% level.

**Semi-parametric Estimation** We can also employ a partially linear semi-parametric estimation to allow for a more flexible relationship between trade credit use and relationship

length.<sup>21</sup> We are particularly interested in documenting whether payment terms change more frequently early on in a relationship, as this would provide strong support to a learning interpretation.

Results are presented graphically in panel A of Figure 3 for the case of Chile. As in Table 4, the underlying estimation controls for exporter-product-destination country and destination country-year fixed effects. Panel A shows the results for the non-parametric part of the regression, where we plot a kernel-weighted local polynomial on the number of transactions within a relationship. The figure shows a steep increase in the use of trade credit at the beginning of the relationship up until about the sixth transaction. After this point, trade credit use only increases slightly. This path is very consistent with a model of Bayesian learning (panel B), where learning is faster early in a relationship and then slows down.<sup>22</sup> The semi-parametric result confirms the prediction in Proposition 4: If the speed of learning declines in the number of transactions, firms should switch more towards trade credit at the beginning of a relationship. The effect is quantitatively meaningful. Based on the semi-parametric estimation, the trade credit share rises by almost 2 percentage points between the first and the fifth transaction.

### 5.3 Additional Results on Relationship Length

In the following, we test the additional predictions of the model on relationship length and its interactions with contract enforcement, product complexity, and markups in Propositions 2 to 4.

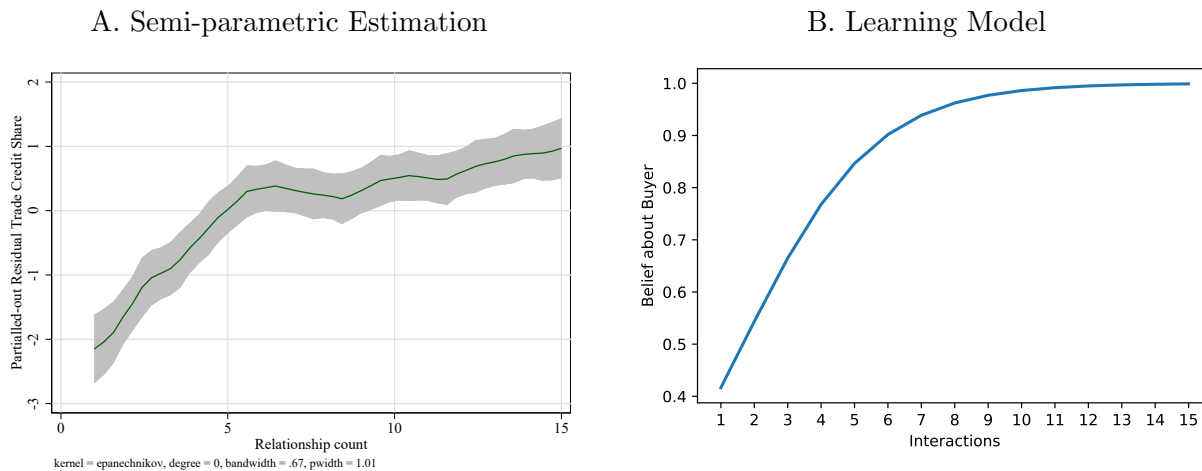
**Relationship Length and Contract Enforcement** We begin by testing Proposition 2, which predicts that the effect of learning on the trade credit choice is larger for source

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<sup>21</sup>The linear part of the estimation considers destination-year and relationship fixed effects, while the non-parametric portion of the model uses an Epanechnikov-kernel-weighted local polynomial to fit the residual trade credit share.

<sup>22</sup>See appendix A.1 for an example of Bayesian learning that can micro-found the assumed learning dynamics and for further details on the simulation that generates panel B.

Figure 3. Trade Credit and Relationship Length: Semi-Parametric Estimation for Chile



*Notes:* Panel A plots the trade credit share against the number of transactions within a relationship for the sample of Chilean exporters. We define relationships in this data as exporter-product combinations in a particular destination country. Panel B illustrates the typical Bayesian learning process (with parameters  $\hat{\eta} = 0.3$  and  $\lambda = 0.6$ , see appendix A.1 for details).

countries with stronger contract enforcement in the case of imports or destinations with weaker contract enforcement in the case of exports. Table 5 presents results from regressions where we interact relationship length with two dummy variables that indicate if a country has a rule of law index above or below the median value in the sample.<sup>23</sup> Results are consistent with the theoretical prediction. In the case of Colombian imports (panel A), the effect of relationship length on the probability of trade credit use is about 40% larger (according to column 4) for source countries with a weak rule of law than for countries with a strong rule of law. This makes sense because the model predicts more cash in advance trade initially when importing from countries with better contract enforcement, leaving more space for learning to shift payments to trade credit over time.

For Chilean exports (in panel B), we find the expected opposite pattern. The effect of relationship length is at least twice as strong for destinations with a weak rule of law than for destinations with a strong rule of law. Even more, in the balanced sample (column 4),

<sup>23</sup>We use the Rule of Law index constructed by the World Bank’s *World Government Indicator* to proxy for the strength of contract enforcement in each country.

relationship length only has a statistically significant effect on the trade credit share in destinations with a weak rule of law.

Table 5. Relationship Length and Contract Enforcement

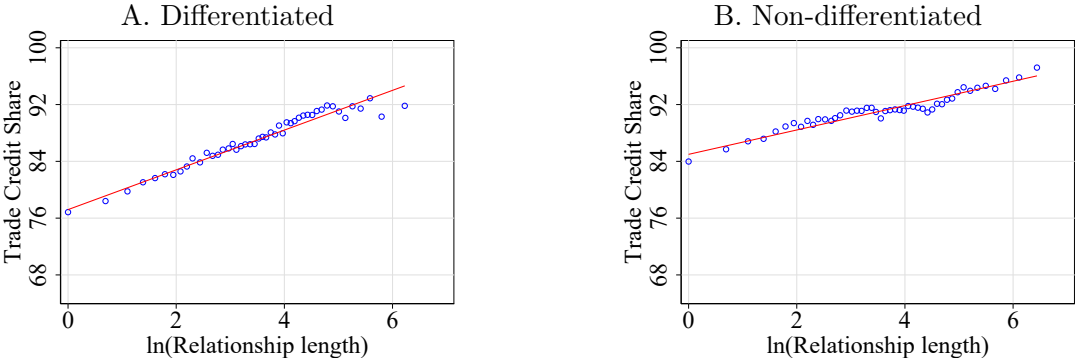
	(1)	(2)	(3)	(4)
<b>A. Colombian Imports</b>				
ln(Relationship Length) $\times$ Low ROL	0.255*** (0.024)	0.546*** (0.023)	0.367*** (0.018)	0.332*** (0.070)
ln(Relationship Length) $\times$ High ROL	0.320*** (0.023)	0.637*** (0.024)	0.461*** (0.018)	0.452*** (0.066)
Sample	All	All	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes	Yes	Yes
Source Country-Year FE	—	Yes	Yes	Yes
Importer-HS10-Year FE	—	—	Yes	Yes
Observations	12,841,920	12,841,694	12,164,002	956,258
<b>B. Chilean Exports</b>				
ln(Relationship Length) $\times$ Low ROL	1.958*** (0.180)	1.216*** (0.199)	1.164*** (0.178)	1.068*** (0.346)
ln(Relationship Length) $\times$ High ROL	0.843*** (0.113)	0.353** (0.154)	0.684*** (0.164)	0.199 (0.266)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	604,843	604,843	604,843	47,177

*Notes:* This table shows the results of a transaction-level regression in which the dependent variable is  $(100 \times)$  a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes interactions between relationship length (measured as the log of the cumulative count of transactions within a relationship) and indicators for whether the source country (in panel A) or the destination country (in panel B) has above or below median values for a rule of law index. Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% level.

**Relationship Length and Product Complexity** Proposition 3 predicts that the effect of learning on the use of trade credit should be stronger for more complex products. We test this prediction measuring product complexity by the degree of product differentiation as defined in Rauch (1999), assuming that differentiated products are more complex than homogeneous products. Figure 4 shows that the positive relationship between trade credit

use and the length of relationships is indeed stronger for differentiated (left panel) than for non-differentiated products (right panel). Table 6 tests the different patterns in a regression framework, interacting the variable for relationship length with dummy variables for differentiated and homogeneous products, respectively. Across all specifications, the effect of relationship length on trade credit is stronger for differentiated products.

Figure 4. Relationship Length and Trade Credit Share by Product Type in Chilean Exports



*Notes:* The figure plots the frequency of use of trade credit account contracts and the length of the buyer-seller relationship. Differentiated products are defined (at the 6-digit HS level) according to the liberal product classification of Rauch (1999). Relationship length is defined as the cumulative number of transactions occurring from the beginning of the relationship.

Table 6. Relationship Length and Trade Credit by Product Type in Chilean Exports

	(1)	(2)	(3)	(4)
ln(Relationship Length) $\times$ Differentiated	1.875*** (0.226)	1.019*** (0.237)	1.093*** (0.242)	1.150*** (0.414)
ln(Relationship Length) $\times$ Homogeneous	1.210*** (0.139)	0.641*** (0.147)	0.825*** (0.130)	0.310 (0.244)
Sample	All	All	All	Balanced
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Exporter-HS8-Year FE	—	—	Yes	Yes
Observations	604,843	604,843	604,843	47,177

*Notes:* This table shows the results of a transaction-level regression in which the dependent variable is  $(100 \times)$  a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes interactions between relationship length (measured as the log of the cumulative count of transactions within a relationship) and indicators for whether the product is differentiated or not. Standard errors (in parentheses) are clustered at the exporter-importer-product level in panel A and at the exporter-product-destination level in panel B. . \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% level.

**Importer Experience, Exporter Experience, and Relationship Length** In line with Proposition 1, we have established that payment terms depend on the length of a relationship between an importer and an exporter. The payment terms could, however, also depend on the experience of an importer sourcing from a certain country (regardless of which exporting firm it trades with) or on how long a firm has been an importer, regardless of where it imports from. Additionally, the foreign exporter’s experience selling to Colombia could affect the payment terms. Our detailed data allows us to disentangle these different effects. In Table 7, we estimate regressions similar to equation 10, adding to the right-hand side the log cumulative number of transactions of an importer (“importer experience”), the log cumulative number of transactions of an importer in a given source country (“country-specific importer experience”), and the log cumulative number of transactions of an exporter in Colombia (“exporter experience”). The results indicate that the most important determinant of the payment contract is the length of a relationship between an importer and an exporter, and not the importer’s or exporter’s experience independently.

Table 7. Importer Experience, Exporter Experience, and Relationship Length in Colombian Imports

	(1)	(2)
ln(Relationship Length)	0.915*** (0.045)	0.706*** (0.050)
ln(Importer Experience)	-0.245*** (0.033)	0.097 (0.100)
ln(Country-Specific Importer Experience)	-0.014 (0.009)	-0.058 (0.058)
ln(Exporter Experience)	-0.478*** (0.045)	-0.412*** (0.119)
Sample	All	Balanced
Importer-Exporter-HS10 FE	Yes	Yes
Source Country-Year FE	Yes	Yes
Importer-HS10-Year FE	Yes	Yes
Observations	12164470	956301
R <sup>2</sup>	0.83	0.82

*Notes:* This table shows the results of a transaction-level regression in which the dependent variable is  $(100 \times)$  a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right-hand side includes measures of relationship length, importer experience, and exporter experience. Standard errors (in parentheses) are clustered at the exporter-importer-product level. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% level.

**Relationship Length and Markups** Finally, we test Proposition 4 to understand whether the learning mechanism dominates the financing cost advantage of trade credit that arises with positive markups when there is a spread between borrowing and deposit rates (see Garcia-Marin et al., 2020, for details). Table 8 presents the results, focusing on the set of relationships that started in 2003 or later to compare the strength of both mechanisms over the full life cycle of a relationship. Consider first columns 1 and 2, which show that both the number of previous interactions and the markup are positive and statistically significant when entering the estimation simultaneously. Magnitudes for the coefficient on log relationship length are similar to those reported in Table 4.



Table 8. Trade Credit, Markup and Relationship Length in Chilean Exports: 2SLS Results

	(1)	(2)	(3)	(4)
ln(Relationship Length)	1.237*** (0.136)	0.623*** (0.151)	1.277*** (0.156)	0.0702 (0.355)
ln(Markup)	6.280** (3.093)	6.738** (3.233)	1.858 (5.261)	11.44** (5.124)
First-Stage F-Statistic	71.0	75.3	118.3	22.5
Relationships	All	All	<10 trades	≥10 trades
Exporter-Destination Country-HS8 FE	Yes	Yes	Yes	Yes
Destination Country-Year FE	—	Yes	Yes	Yes
Observations	202,507	202,507	109,950	92,557

*Notes:* This table shows the results of a transaction-level regression in which the dependent variable is  $(100 \times)$  a dummy variable equal to one for transactions financed with trade credit and zero otherwise. The right side of the regression includes relationship length and firm-product markups. All columns use firm-product TFPQ to instrument for markups. The table only shows second-stage results (together with the corresponding cluster-robust Kleibergen-Paap rKWald F-statistic). The Stock-Yogo value for 10% maximal IV bias is 16.4. Markups are computed at the firm-product level (products are defined at the 5-digit CPC level). Column 1 controls for the logarithm of firm employment. Standard errors (in parentheses) are clustered at the firm-product-destination level. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% level.

Proposition 4 predicts that the effect of learning on the trade credit choice declines in the number of transactions while the effect of the markup increases. To test these predictions, we split the data into two samples: the first 9 transactions in a relationship and all trades after the first 9 transactions. Results are presented in columns 3 and 4 of Table 8. For the first nine trades, the coefficient on relationship length is twice as large as the average effect in column 2, while the coefficient on markups turns insignificant (column 3). In contrast, when we move beyond the ninth transaction (column 4), the coefficient on relationship length is no longer significant – with a magnitude very precisely estimated at zero, – while the positive coefficient on markups becomes statistically significant and is 50 percent larger than the average effect estimated in column 3. These results suggest that in line with Proposition 4, the effect of learning is more important at the beginning of a relationship. At the same time, the financing cost advantage of trade credit, captured by markups, matters more in older relationships.

## 6 Concluding Remarks

Exploiting Colombian and Chilean transaction-level trade data, this paper documents new facts about trade credit use: Trade credit use increases with firm-to-firm relationship length, an effect that is stronger for destination (source) countries with weaker (stronger) contract enforcement, and for trade in differentiated goods.

We present a model featuring enforcement frictions, learning, and a financing cost advantage of trade credit that can rationalize these patterns. Initially, as there is uncertainty about the reliability of the trading partner, payment risk is a key factor limiting the use of trade credit. Through learning this uncertainty resolves within a relationship over time. For older relationships, the payment choice is therefore only determined by the financing cost advantage of trade credit and all relationships rely on trade credit in the long run.

These findings add to our understanding of the importance of relationships for international trade. As earlier work has shown, long-term relationships are more stable and more resilient in crisis times ([Monarch and Schmidt-Eisenlohr, 2018](#)), are better able to share risk in the presence of exchange-rate shocks ([Heise, 2015](#)), and can overcome enforcement frictions ([Macchiavello and Morjaria, 2015](#)). This paper shows how long-term relationships can help save on financing costs by employing the more efficient payment term, trade credit. This additional channel underscores the centrality of long-term relationships for the stability of international trade and global value chains.

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# A Theory Appendix

## A.1 Micro Foundation: A Learning Model

In this section, we discuss an example of a learning model that can micro-found the dynamics discussed in Section 2. The below exposition is based on [Monarch and Schmidt-Eisenlohr \(2018\)](#) and [Araujo et al. \(2016\)](#).<sup>1</sup> We use the same setup as in the baseline model with two types of firms: reliable and unreliable.  $\lambda$  and  $\lambda^*$  now reflect the probability that the seller or buyer do not have an opportunity to cheat in a given period. Let  $\hat{\eta}$  denote the population mean of reliable firms.

**Bayesian Updating** Initially, a seller believes (correctly) that the probability a buyer is reliable is equal to the population mean,  $\hat{\eta}$ .<sup>2</sup> Every period that a relationship survives, the seller updates her belief about the buyer according to Bayes' rule. A successful interaction signals that the buyer is either reliable or did not have an opportunity to cheat. Learning is therefore not instantaneous but takes time. However, learning is the fastest initially, as the probability that the trading partner is unreliable is the highest then.

If a seller has successfully sold to a buyer for  $k$  periods, the posterior probability that the buyer is reliable can be derived as:

$$\eta_k = \frac{\hat{\eta}}{\hat{\eta} + (1 - \hat{\eta}) \lambda^k}. \quad (1)$$

Importantly, the probability only changes with the length of time that a seller has been selling to the same buyer. It is easy to see that for large  $k$ ,  $\eta_k$  converges to 1; that is, the seller is almost certain that the buyer is reliable. To shed further light on this, we can take the derivative of  $\eta_k$  with respect to  $k$ :

$$\frac{\partial \eta_k}{\partial k} = -\ln(\lambda) \hat{\eta} (1 - \hat{\eta}) \left( \frac{1}{\hat{\eta} + (1 - \hat{\eta}) \lambda^k} \right)^2 \lambda^k > 0 \quad (2)$$

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<sup>1</sup>See also [Antràs and Foley \(2015\)](#) and [Macchiavello and Morjaria \(2015\)](#) for similar setups.

<sup>2</sup>In this section, we drop the star superscript for buyers.

Not surprisingly, this derivative is always positive. That is, with every successful interaction, the seller's belief about the buyer's reliability improves. Now, taking the second derivative delivers:

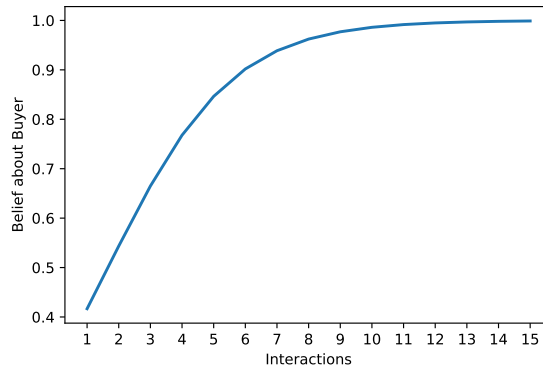
$$\frac{\partial^2 \eta_k}{\partial k^2} = -(\ln(\lambda))^2 \hat{\eta} (1 - \hat{\eta}) \lambda^k \left[ \frac{1}{\hat{\eta} + (1 - \hat{\eta}) \lambda^k} \right]^2 \frac{\hat{\eta} - (1 - \hat{\eta}) \lambda^k}{\hat{\eta} + (1 - \hat{\eta}) \lambda^k}, \quad (3)$$

which is smaller than zero for all  $k$  if

$$\hat{\eta} > \frac{\lambda}{1 + \lambda}. \quad (4)$$

That is, as long as condition (4) holds, the second derivative of the belief with respect to  $k$  is negative and the learning speed declines over time. Below, we present a graphical example on how learning looks like in this environment where we pick  $\hat{\eta}$  such that condition (4) holds.

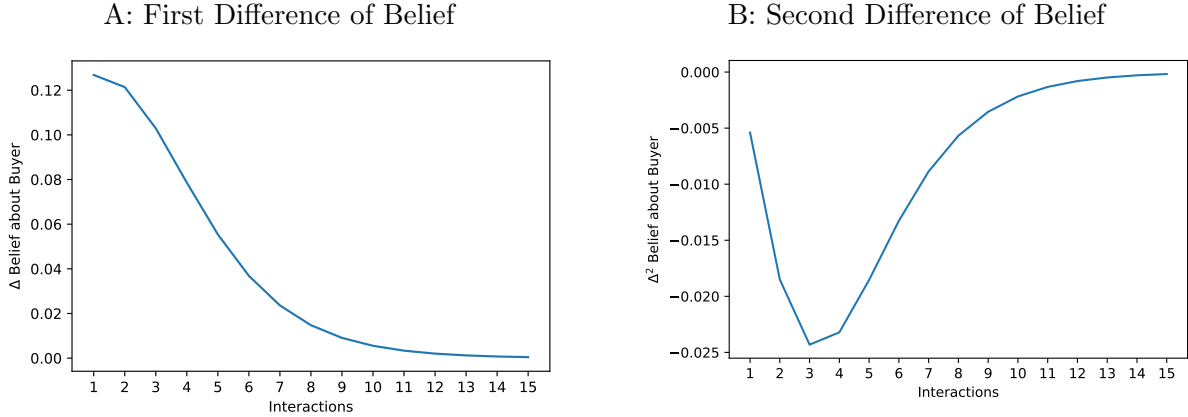
Figure A.1. Bayesian Learning: Level of Belief



*Notes:* This figure illustrates the learning process in our example. Parameters are:  $\hat{\eta} = 0.3$  and  $\lambda = 0.6$ .



Figure A.2. Bayesian Learning: Speed of Learning



*Notes:* This figure illustrates the speed of learning in our example. Panel A shows the first difference in the belief about the buyer. Parameters are:  $\hat{\eta} = 0.3$  and  $\lambda = 0.6$ .

The above discussion showed how learning about the buyer works when transactions are done with trade credit and the buyer has an incentive to deviate from the contract. To generate two-sided learning in this setup, there also needs an opportunity to deviate for the seller under trade credit. This could be modeled by following [Antràs and Foley \(2015\)](#) and allowing the seller to default on the bank loan that she draws to pre-finance production costs. In that case, if defaults to the bank are public information, the buyer learns about the seller even in the case of trade credit. The reverse mechanism would hold for the seller learning about the buyer with cash in advance.

## B Empirical Appendix

### B.1 Markups Estimation

To test the financing motive for trade credit use, we construct markups at the firm-product-year level following the production-based approach by [De Loecker et al. \(2016\)](#). This methodology requires minimal working assumptions, is flexible about the underlying demand system, and delivers a simple representation of the price-cost markup, which equals the ratio

between the output elasticity of product  $p$  with respect to a flexible input  $V$  ( $\theta_{ipt}^V$ ), and the expenditure share of the flexible input  $V$  (relative to the sales of product  $p$ ;  $s_{ipt}^V$ ). While the latter element is readily available in our data, the input-output elasticity requires estimating the production function. For this, we specify a Cobb-Douglas production function using labor, capital, and materials as production inputs to produce each output  $p$ . To avoid the so-called input and output price biases (see [De Loecker and Goldberg, 2014](#), , for details), we measure output and material expenditure in physical units using firm-specific price deflators. The identification of the production function coefficients in multi-product firms directly follows [De Loecker et al. \(2016\)](#) and requires assuming that single- and multi-product firms use the same technology to produce each product  $p$ . Hence, we identify the production function coefficients for all firms-products using the subset of single-product firms.<sup>3</sup> We estimate the production function coefficients following the methodology proposed by [Akerberg et al. \(2015\)](#) to control for the endogeneity of firms' inputs choice.<sup>4</sup>

The second component needed to compute markups is the expenditure share, which is only directly available at the firm level. To compute this element at the firm-product level, we follow [Garcia-Marin and Voigtländer \(2019\)](#) assuming that firms allocate inputs in the same proportion across outputs. Under this assumption, we can take advantage of a unique feature of ENIA that provides information on total variable costs (labor cost and materials) for each product the firms produce to compute product-specific input usage. Once we obtain the levels of inputs for each firm-product, we compute the expenditure share by dividing the value of material inputs by product-specific revenues. [Table B.1](#) shows summary statistics for the estimated markups

Note that output and input products are defined according to the Central Product Clas-

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<sup>3</sup>The main limitation of this approach is that it restricts economies of scope on the production side, but as [Garcia-Marin et al. \(2020\)](#) show for the same data we use in this paper, considering alternative markup measures not subject to this issue (such as reported average costs and firm-level markups) lead to similar results when analyzing the financing motive for trade credit use.

<sup>4</sup>In addition, we allow past exporting and investment decisions to affect firms' productivity and include the probability of remaining single-product to correct for the bias that results from firm switching non-randomly from single to multi-product production (see [De Loecker et al., 2016](#), for details).

sification (CPC) at the 8-digit level, identifying 1,190 products over 2003-2007.<sup>5</sup> To ensure a consistent dataset, we follow several steps, including the deletion of observations that have missing, zero, or implausible variation in the values of any of the main variables.

Table B.1. Summary Statistics Estimated Markups

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Markups (in logs)	0.153	0.373	-0.125	0.105	0.383	26,584

*Notes:* The table lists summary statistics for the estimated markup. Markups are computed for the universe of Chilean manufacturing exporters that can be matched to the Chilean Annual Manufacturing Survey (ENIA), over the period 2003-2007.

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<sup>5</sup>For example, CPC disaggregates the wine industry (ISIC 3132) into 4 different categories: “Sparkling wine”, “Wine of fresh grapes”, “Cider”, and “Mosto”.